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Chapter 3

LONGITUDINAL ASSESSMENT OF CHANGES IN JOB PERFORMANCE AND WORK ATTITUDES: CONCEPTUAL AND METHODOLOGICAL ISSUES

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In industrial and organizational (I/O) psychology, we are often interested in systematic intra-individual changes in job performance (e.g., task performance, contextual performance) or work attitudes (e.g., organizational commitment, withdrawal behaviors). Indeed, many research areas are explicitly about the intra-individual changes and processes that unfold in various ways over time (e.g., learning and skill acquisition, newcomer socialization). Consistent with the focus on these intra-individual change phenomena, the past two decades of the I/O psychology literature has seen a sustained interest in conceptual and methodologic issues relating to the longitudinal assessment of various facets of changes over time (e.g., Bliese, Chan, & Ployhart, 2007; Chan, 1998a, 2011; Chan & Schmitt, 2000; Hofmann, Griffin, & Gavin, 2000; Hofmann, Jacobs, & Baratta, 1993; Wang & Chang, in press).

There are various complexities in understanding changes over time including issues of levels of analysis, measurement error, multivariate modeling, and types of change in the focal variable. For example, the process of change may exist at one or more of multiple levels of analysis, such as at the individual, the group, or the organizational level. This raises fundamental construct validity issues (i.e., issues of composition models, see Chan, 1998b) such as whether the same or different constructs are being conceptualized and assessed at different levels, the functional relationships linking the constructs at the different levels, and whether the same or different processes of changes over time or inter-construct relationships are occurring at different levels. Changes over time may also exist in complex ways in cross-levels situations. For example, changes over time at one level may affect the changes over time or eventual outcome

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at another level. Another type of cross-levels situations concerns changes over time in an inherently cross-levels construct such as person–group fit (a composite construct consisting of the lower level person component and the higher level group component), which raises issues of how different rates of change or different types of change occurring at different levels (or components) impact on the cross-levels (composite) construct. More fundamentally, any observed changes over time need to be decomposed into random fluctuations versus systematic changes in the focal variable. When systematic change over time exists, the trajectory of a variable may have time-varying correlates and the trajectory may affect or be affected by the trajectories of other variables, such that we need multivariate models that specify and test relationships linking changes in different focal variables. The type of change that the focal variable is undergoing may be changes in quantitative level, qualitative status, or a mixture of both. Finally, there may be between-group differences in one or more of the various facets of changes over time, and these groups may be observed groupings such as gender and culture groups or unobserved (or latent) groupings distinguishable by distinct characteristics of changes over time.

Understanding the above complexities and the various facets of change over time, in terms of both the conceptual and methodologic considerations, is necessary in order to make adequate substantive inferences from the longitudinal assessment of changes in job performance, work attitudes, or other focal variables. The purpose of this chapter is to provide a state-of-the-art review of the conceptual and methodologic advances in understanding changes over time, with a focus on future research challenges and directions on substantive applications to studies of job performance and work attitudes.

MULTILEVEL ISSUES

Many phenomena in I/O psychology research are inherently multilevel. With conceptual and methodologic advances in multilevel analysis (e.g., Chan, 1998b; Kozlowski & Klein, 2000; Morgeson & Hofmann, 1999), more studies are attempting to model multilevel phenomena. The bulk of the multilevel research in I/O psychology discusses the "traditional" type of multilevel data in which individuals are nested within groups. In modeling changes over time using longitudinal data, we are in fact dealing with a type of multilevel data in which the multilevel structure is less obvious. Longitudinal data are obtained from measurements repeated on the same individuals over time, and hence a multilevel structure is established with the repeated observations over time (Level 1) nested within individuals (Level 2).

While the multilevel analysis of cross-sectional grouped data is concerned with inter-individual differences associated with group membership, multilevel analysis of longitudinal data is concerned with modeling intra-individual change over time. Although multilevel regression models can also be used to analyze these changes over time (e.g., Bryk & Raudenbush, 1992), the issues of changes over time are often very complex and may involve facets of change over time (e.g., conceptual changes in the constructs, changes in calibration of measurement, various types of time-related error-covariance structures) that are not readily handled by multilevel regression models. In modeling change over time, we are primarily concerned with describing the nature of the trajectory of change and accounting for the inter-individual differences in the functional forms or parameters of the trajectories by relating them to explanatory variables. The explanatory variables may be in the form of experimentally manipulated or naturally occurring groups, time-invariant predictors, time-varying correlates, or the trajectories of a different variable. Latent growth modeling (LGM) and its extensions are well suited to address these issues. Chan (1998a) provided a detailed review of these issues and the application of LGM techniques, as well as an overview comparison between latent variable models and multilevel regression models. Developments in latent variable analysis, particularly structural equation modeling, have been successfully applied to modeling the complexities involved in a variety of these changes (see Chan, 1998a, 2002a,b, 2005; Singer & Willet, 2003).

Duncan, Duncan, and Strycker (2006) provided a concise introduction to the technical issues involving analysis of data with complicated hierarchical structures combining intra-individual changes over time with two or more additional levels (e.g., individual, team, and organizational levels) and demonstrated how multilevel latent growth models can be applied to such data sets. However, despite the separate advances in multilevel research and longitudinal assessment of change, there is a lack of integration of the advances in these two areas and several important multilevel issues in modeling changes over time have not received sufficient, if any, attention. I classify these issues broadly into three categories:

1. Modeling changes over time at multiple levels;
2. Modeling cross-levels effects of changes over time; and
3. Modeling dynamic cross-levels constructs.

These issues are explicated in the following sections.

Modeling Changes Over Time at Multiple Levels

Traditionally, the majority of the research on job performance and work attitudes (e.g., personnel selection, performance appraisal, job satisfaction, work motivation) has approached the focal constructs or phenomena under investigation from a micro perspective that focuses almost exclusively on individual-level variables such as the individual's abilities, job performance, and work perceptions. However, many constructs and phenomena of interest examined by I/O psychologists are in fact multilevel in nature involving multiple levels of analysis such as the individual, group, and organization. Often, a higher level construct (e.g., team performance) is composed by aggregating (in one of several methods) the units at the lower level construct (e.g., each team member's job performance). Correspondingly, the process of changes over time may exist at one or more of multiple levels of analysis, such as at the individual level and team level.

The adequate examination of multilevel constructs and data sets involve addressing complex conceptual, measurement, and data analysis issues. Several researchers have developed useful organizing frameworks that help to clarify conceptualizations and decide on measurements or operationalizations of similar constructs at multiple levels, as well as identify the types of relevant evidence to support the multilevel hypotheses. Specifically, in the last two to three decades, many I/O psychologists have contributed to multilevel research by developing conceptual organizing frameworks (e.g., Chan, 1998b; Kozlowski & Klein, 2000; Morgeson & Hofmann, 1999; Rousseau, 1985) and many scholars have helped advance multilevel research by providing relatively nontechnical summaries and applications of existing multilevel analytical strategies (Bliese, 2000; Bryk & Raudenbush, 1992) which helped users in I/O psychology to apply appropriate techniques to their multilevel data sets. For a summary of these conceptual bases and analysis issues concerning multilevel analytical strategies, see Chan (2005).

Composition models (Chan, 1998b; Rousseau, 1985) address fundamental construct validity issues by specifying the functional relationships linking the constructs at the different levels that reference essentially the same content but are qualitatively different at different levels (e.g., self-efficacy versus team efficacy). In Chan's (1998b) typology of composition models, four of the five models (i.e., additive, direct consensus, referent-shift consensus, dispersion) have received much attention and have been applied in the past decade of multilevel studies. A common feature across these four composition models is that they are all focused on the *static* core attributes of focal constructs (e.g., efficacy perceptions), which describe some stable units or state of affairs at the individual or higher level. While these four models are fundamental and one or more of these models are necessary in composing the lower level construct to the higher level construct, they do not directly provide the essential conceptual basis for composing the process of changes over time at the lower level to the higher level. The fifth model in Chan's typology, namely process composition, provides this basis.

Process composition models are concerned with composing a process or mechanism from the lower level to the higher level, and are therefore well suited to examining changes over time at multiple levels in so far as changes over time are construed as processes or mechanisms that unfold over time. In a process composition model for changes over time, the change process or mechanism is first specified at the lower level explicating the essential or critical parameters and their interrelationships. The change process then is composed to the higher level by identifying critical higher level parameters, which are higher level analogs of the lower level parameters, and describing interrelationships among higher level parameters, which are homologous to the lower level parameter relationships. To illustrate, two examples are provided below.

An example of process composition of changes over time is a simple learning process in performing a task being composed from the individual level to the team level. At the individual level, the trajectory of change over time in task performance follows a functional form characterized by an initial period of linear increase in performance levels at a constant rate of change, an intermediate period of increase in performance levels at a decreasing rate of change, and a final maintenance period of no change in performance levels. Throughout the entire change period, the same construct of task performance is assumed to be measured and with the same precision, in the sense that there are no changes in the conceptual domain of the construct being measured nor changes in the calibration of the measurement. In other words, there is measurement invariance across time in that any difference in performance levels between two time points represents meaningful change and the magnitude of change may be directly interpreted as a change in the absolute level of task performance.

In this example of simple process composition of performance changes over time, task performance at the team level is construed to change over time following a similar trajectory as that of the individual level, with the same assumptions of measurement invariance across time. That is, the individual level of performance changes over time is composed to the team level such that the critical parameters are analogous across the individual and team levels. The critical parameters are assumptions of measurement invariance across time and the functional form of the trajectory represented by the direction and rate of changes in performance levels over the entire change period. In terms of analysis, structural equation modeling may be used to test for measurement invariance across time at each of the two levels. After measurement invariance over time has been established, LGM or other techniques of longitudinal analysis (e.g., multilevel latent variable modeling) may be used to identify and test whether the functional forms of the change trajectory are similar or different across the two levels, depending on the substantive hypotheses concerning between-levels differences in the directions and rates of change in performance changes over time.

A more complex example of process composition of changes over time is in the study of development of (i.e., changes over time in) efficacy perceptions about the team at both the individual and team levels. In research on work teams (e.g., Guzzo, Yost, Campbell, *et al.*, 1993), efficacy perceptions at the team level is often a case of referent-shift consensus composition (Chan, 1998b). The composition starts with the individual-level construct of self-efficacy. Self-efficacy is defined as an individual's belief and confidence in mobilizing his or her resources for successful task performance (an example item is "I am confident that I can perform this task."). A new form of the construct at the same level (i.e., individual level) is then derived by shifting the referent in the efficacy perception from the self to the team as a whole (an example item for the new form of the construct is "I am confident that my team can perform this task."). The new construct, namely collective efficacy, is defined as the individual team member's belief and confidence that the team can mobilize its resources for successful task performance. Note that collective efficacy is still at the original individual level of conceptualization (Guzzo, Yost, Campbell, *et al.*, 1993). Within-group consensus (as indexed by within-group agreement of individuals' perceptual scores) is used to justify the aggregation of individuals' collective efficacy perceptions to represent the value of the higher level (i.e., group level) construct called team efficacy.

In this example, assume that the researcher is examining how team members' collective efficacy perceptions change over time, and is interested in describing the process in which the team progressively changes from the state of lack of within-group agreement of individual-level collective efficacy perceptions to the state of high within-group agreement. That is, the researcher wants to compose a team-level process of team efficacy emergence. To do so, the researcher first specifies an individual-level process describing how an individual develops collective efficacy perceptions. For simplicity, assume the researcher has a theory that development of collective efficacy is an integration process, moving from an initial state in which the individual's distinct efficacy beliefs about the team's ability in accomplishing distinct aspects of the task are unrelated or, at best, loosely interrelated through progressive states in which these separate beliefs become increasingly interrelated to the eventual state in which they become integrated into a single global belief. This integration process, which describes the nature of the changes over time in collective efficacy perceptions at the individual level, is composed to the higher level to specify the process of team efficacy emergence. That is, the researcher could specify team efficacy emergence as an integration process, moving from an initial state in which there is little agreement among individuals' collective efficacy perceptions, through progressive states in which the level of agreement gradually increases, to the eventual state in which high agreement is achieved. Note that within-group agreement is a higher level analog of intra-individual correlation of collective efficacy beliefs of the team's ability in accomplishing distinct aspects of the task. Similarly, the notion of increasing levels of within-group agreement as a team progresses over time is analogous to the notion of increasing inter-correlations among distinct collective efficacy beliefs as an individual progresses over time. The initial and final states of the team also are analogous to the respective states of the individual. In short, critical parameters of the integration process at the individual level have higher level analogs that constitute the critical process parameters at the team level.

In this team efficacy emergence example, the within-group agreement index is the higher level operational analog of the correlation coefficient. Note that the within-group agreement index is used here as a dispersion measure (assessing team efficacy strength at multiple points in time) as opposed to a statistical criterion for aggregation. The integration process in team efficacy emergence can be construed as changes in team efficacy strength (as opposed to team efficacy level; i.e., intra-team changes in variance as opposed to intra-team changes in means). Hence, when moving from the source construct of collective efficacy to the higher level process of team efficacy emergence, a dispersion composition (from collective efficacy to team efficacy strength) precedes the process composition. As noted in Chan (1998b), a theory of the focal construct in a multilevel study may contain several composition forms.

In terms of analysis, nested model comparisons using longitudinal confirmatory factor analysis may be used to test for changes over time in the factor structure of efficacy beliefs at each of the two levels. The hypothesized integration process of change over time would test for the fit of a longitudinal confirmatory factor analytic model (and compare it against competing models) that specified different theory-driven factor structures corresponding to initial, intermediate, and final time periods. Specifically, we expect a factor structure of distinct and uncorrelated or lowly correlated efficacy beliefs in the initial period, a factor structure of moderately correlated efficacy beliefs in the intermediate period, and factor structure of highly correlated efficacy beliefs or a single global factor of efficacy beliefs in the final period (for technical issues of analysis, see Chan, 1998a).

The above conceptual and methodologic principles relating to process composition to model changes over time at multiple levels may be applied to a variety of substantive research areas in job performance and work attitudes, such as changes in levels and dimensionality of performance, organizational citizenship behaviors (OCBs), cohesion, withdrawal behaviors, cynicism, commitment, and organizational climate.

Modeling Cross-levels Effects of Changes Over Time

In addition to occurring at multiple levels, changes over time may occur in complex ways in cross-levels situations. There are two types of cross-levels situations that have not received sufficient attention in the literature. This sub-section and the next address these two types of situations, respectively.

Almost all cross-levels situations in multilevel research refer to cross-levels effects in which the predictor or causal variable is at one level and the criterion or effect variable is at a different level (higher or lower level than the predictor or casual variable). Cross-levels effects involving changes over time are complex because the focal construct represented by the predictor/causal variable, the criterion/effect variable, or both, are not static. In fact, the values on the variable representing changes over time are not the absolute magnitude on the focal construct assessed by the static variable as indicated by the cross-sectional measurement. Instead, the values representing changes over time are growth parameters that describe the nature of the change trajectory including the rates of change (e.g., magnitude of the slope in a linear growth) or shape of the trajectory (e.g., quadratic function).

In the vast majority of studies examining cross-levels effects that involve changes over time, the purpose has been to estimate the predictive or causal effect of a time-invariant (i.e., static) individual difference variable (e.g., cognitive ability or personality traits) on the inter-individual differences in intra-individual changes over time in the criterion or effect variable (e.g., Hofmann, Jacobs, & Baratta, 1993). The research strategy is focused on measuring the rate of change in the criterion/effect variable being tracked over time (e.g., inter-individual differences in the slope of job performance). That is, changes over time are treated as endogenous in the model and often at the lower level (intra-individual level represented by the repeated observations within an individual). The predictor/causal variable, on the other hand, is treated as exogenous and often at the higher level (individual level represented by the inter-individual differences on the trait construct). That is, the cross-levels effect is a downward effect represented in the model by a unidirectional path from the predictor at the higher level to the criterion (i.e., changes over time) at the lower level. This conceptualization fits nicely into the traditional hierarchical linear modeling (HLM) analytic framework used in multilevel research in which the individual (i.e., trait) is treated as a time-invariant predictor at the higher level (Level 2) accounting for (causing or predicting) the intra-individual changes over time occurring at the lower level (Level 1, which is nested under Level 2).

In the HLM analytic framework, inter-individual differences in intra-individual changes over time is conceptualized as a growth parameter to be explained (predicted or caused) by other variables (i.e., treated as endogenous). The HLM technique is not suited to conceptualize the growth parameter representing these changes over time as an exogenous variable that explains (predicts or causes) other variables. Clearly, whether changes over time should be conceptualized as exogenous or endogenous should not be determined by what a chosen analytical technique can or cannot do, but should be determined by theory, as translated into conceptual model linking changes over time to other variables.

Consider a theory of newcomer adaptation which states that while newcomers follow a linearly increasing trajectory in their intra-individual changes in job performance over time during the transition period (e.g., first 3 months in the organization), those who increased their performance at a faster rate (i.e., a higher slope of performance) will be assessed by their supervisors after the end of the transition period to have a higher potential to advance in the organization. In the conceptual model derived from this theory, the growth parameter representing intra-individual changes in performance over time is an exogenous variable that accounts for (causes or predicts) the supervisory assessment of potential. In this example, changes over time occur at the lower (i.e., intra-individual) level and supervisory assessment of potential is the criterion at the higher (i.e., individual) level. That is, the cross-levels effect is an upward effect represented in the model by a unidirectional path from the predictor (i.e., changes over time) at the lower level to the criterion at the higher level.

The LGM framework has the flexibility to represent changes over time as either exogenous or endogenous. Hence, the analytic framework is well suited to model upward cross-levels effects in which changes over time occurring at the intra-individual (lower) level account for the individual (higher) level variable. Specifically, the hypothesized LGM would specify a structural unidirectional path from the growth parameter to the individual-level criterion variable (in this example, supervisory assessment of potential).

In the newcomer adaptation example, we could extend the theory by stating that newcomers with higher cognitive ability will be assessed by their supervisors after the end of the transition period to have a higher potential to advance in the organization due to their higher rate of change in performance over the transition period. In other words, the relationship between newcomer cognitive ability and supervisory assessment of potential is mediated by intra-individual changes in performance over time. In this conceptual model, there is a downward cross-levels effect represented by a unidirectional path from cognitive ability at the higher (individual) level to the performance changes over time at the lower (intra-individual) level, as well as an upward cross-levels effect represented by a unidirectional path from performance changes over time at the lower (intra-individual) level to potential at the higher (individual) level. To test this conceptual model, an LGM specifying these two structural unidirectional paths to represent the mediation effect could be fitted to the data.

In addition to serving either as a predictor or a mediator, the growth parameter can serve as a moderator in a cross-levels effect situation. For example, we could extend the theory of newcomer adaptation to state that the strength of the positive relationship between newcomer impression management tendency (individual level) and supervisory assessment of potential (individual level) is moderated by newcomer performance changes over time (intra-individual level). In this example, a cross-levels effect occurs because the moderator is at a lower level than the level of the two variables with their relationship being moderated. In principle, this moderator effect can be tested by fitting an LGM in which the growth parameter interacts with the impression management variable to affect the potential assessment variable. In practice, testing this moderator effect may face certain analytic challenges due to technical difficulties associated with incorporating nonlinear functions involving continuous variables in latent variable models generally and latent growth models specifically, although there have been significant advances in methods for testing interactions involving latent variables (e.g., Joreskog & Yang, 1996; Wen, Marsh, & Hau, 2002). An alternative and easier way is to adopt a two-step approach to the analysis, by first using LGM to obtain the newcomer's score on the growth parameter (i.e., slope) and next, using moderated regression analysis, regress the criterion variable (i.e., potential) on the growth parameter, impression management, and the growth X impression management interaction term. This moderated regression tests the hypothesis that the strength of the relationship between impression management and potential is moderated by performance changes over time (i.e., the growth parameter).

To summarize, cross-levels effects involving changes over time may occur in different ways. Although most commonly studied as such, the cross-levels effect need not always be a downward effect represented in the model by a unidirectional path from the predictor at the higher (individual) level to the criterion (i.e., changes over time) at the lower (intra-individual) level. As shown in this sub-section, cross-levels effects could be upward, represented by unidirectional paths from changes over time at the lower level to the criterion variables at the higher level. In addition, changes over time need not always be the criterion variable in the cross-levels effect relationship – it could be the predictor, mediator, or moderator. It is theoretically reasonable to expect that intra-individual changes over time in performance or work attitudes could have causal or predictive efficacy in accounting for individual level variables. By reconceptualizing intra-individual changes over time from a criterion variable to a predictor, mediator, or moderator variable, we are likely to open new and fruitful avenues for substantive research.

Modeling Dynamic Cross-levels Constructs

Another type of cross-levels situation in changes over time concerns dynamic cross-levels constructs. Unfortunately, discussions on this important aspect of change over time are virtually absent in the literature on longitudinal assessment. This somewhat surprising neglect needs to be addressed, particularly in I/O psychology where many study variables are inherently cross-levels constructs and the real-world phenomena that they represent outside the study are dynamic in nature (i.e., changes over time do occur).

In I/O psychology, the prototypical examples of cross-levels constructs are person–environment (P-E) fit constructs such as person–job fit, person–group fit, and person–organization fit (for review of P-E fit constructs, see Edwards, 1994; Kristof, 1996). P-E fit constructs are inherently multilevel in nature. A cross-levels construct (Chan, 1998b), such as person–group fit, is a composite construct consisting of a lower level component construct (in this example, the person-level construct) and a higher level component construct (in this example, the group-level construct). A cross-levels construct is dynamic when one or both of the level construct changes over time. Dynamic cross-levels constructs are complex and they raise critical issues regarding how different rates of change or different types of change may occur at different levels (or components) and how these differential changes impact the cross-levels (composite) construct.

Theories and research on job performance and work attitudes, and more generally in the areas of recruitment, selection, classification, training and development, appraisal, and turnover, are inextricably linked to studies on P-E fit in so far as the investigation is focused on the match between the person and the work environment in which the person functions. In such studies, the nature of the P-E fit construct, as well as its predictive validity, is dependent on both the nature of the person constructs and the environment constructs in question. Clearly, any longitudinal changes in either the person level construct or environment level construct will have an impact on the P-E fit construct. Hence, dynamic cross-levels constructs such as dynamic P-E fit constructs pose important conceptual and methodologic challenges that need to be adequately addressed if we are to make substantive inferences from P-E fit studies.

In any P-E fit study, the type of fit may be construed as complementary fit or supplementary fit. Complementary fit is concerned with the match between the nature of the needs or capabilities of the person and what the environment offers to or requires of the person. For example, the organization may demand time and ability, and the extent to which the employee supplies these resources affects complementary fit. Supplementary fit is concerned with the similarity in values, beliefs, and other characteristics between the person and the organization. For example, the extent to which employees with creative interests have the opportunity in the organization to engage in unstructured and unconventional activities affects supplementary fit.

Changes over time in either the person or organization levels could affect the cross-levels P-E fit construct in various ways. Consider the situation of high complementary fit between a person's cognitive ability and the ability demands required from the work environment. Assuming that the person's cognitive ability remains constant over the time period in question, changes over time in the magnitude or type of work environment demands (e.g., the level of the ability demands of the environment increased or decreased considerably; new non-ability demands emerged in the environment) could lead to intra-individual changes in P-E fit (in this example, P-E fit decreases over time) even while the trait levels of individuals remain constant over time. This has direct implications and challenges for developing practical recommendations for recruitment and selection (using trait levels of individuals) when the empirical basis is constituted by the findings from cross-sectional (static) assessment of P-E fit. The problem gets more complicated when changes over time are occurring at both the person and environment levels, and especially when the rates of change and even nature of change over time (e.g., functional form of the trajectory, dimensionality of the construct) differ between levels. Similar issues apply to supplementary fit if the fit construct is dynamic.

In short, when a P-E fit construct is in fact dynamic (i.e., changes over time), a static representation of the P-E fit construct obtained from the cross-sectional assessment is likely to result in misleading substantive inferences and practical recommendations. It is also important to note that although high P-E fit is generally predictive of positive outcomes, it is not true that fit is inherently adaptive nor is misfit inherently maladaptive. Construct-oriented studies need to be undertaken to address cutting edge research questions concerning when and how fit may have negative effects (e.g., through group-think processes) and misfit may have positive effects (e.g., through innovative ideas), and these questions can only be adequately addressed by explicating the nature of the constructs and construct relationships involved, as well as the degree and type of changes over time that may occur in the lower level (person) and higher level (environment) components of the cross-levels fit construct.

Static cross-levels constructs such as P-E fit constructs are typically analyzed using polynomial regressions (e.g., Edwards, 1994) or hierarchical multiple regressions to test the P-E interaction term representing the P-E fit construct (e.g., Chan, 1996). However, these techniques are not well suited to model dynamic cross-levels constructs because they were not developed to directly assess the various facets of intra-individual changes over time (Chan, 1998a). Given the lack of conceptual attention given to dynamic cross-levels constructs, it is not surprising that methodologic or data analysis discussions on longitudinal modeling have not explicitly discussed the assessment of dynamic cross-levels constructs. Fortunately, advances in LGM, with its multilevel, multivariate, and multiple group extensions, could provide a unified and flexible approach to model the various facets of changes in dynamic cross-levels constructs including both changes in the cross-levels construct and the correlates of these dynamic changes (i.e., causes or predictors of longitudinal changes in the cross-level constructs and the impact that these changes have on other constructs). LGM could also be combined with longitudinal confirmatory factor analyses methods and measurement invariance analyses to assess changes in dimensionality over time for each level component of the cross-levels construct. For a review of LGM and its extensions, see Chan (1998a; 2002a) and Duncan, Duncan, and Strycker (2006).

MULTIVARIATE ISSUES

Before one selects the appropriate technique for analyzing a longitudinal data set, the specific question about the change over time in the longitudinal process must be explicated (Chan, 1998a). These questions may be broadly classified into descriptive and explanatory questions. The descriptive question asks how the repeatedly measured unit of analysis (e.g., individual, group, organization) changes over time on one or more focal variables (e.g., job performance, group cohesion, organizational climate for safety). For example, in a study of changes in job performance over time, we may ask if the performance change is "reversible." That is, does the trajectory of performance change follow some monotonically increasing or decreasing (e.g., linear) functional form that represents an irreversible (at least within the longitudinal time period studied) change or some non-monotonic functional form (e.g., an "inverted U") that represents reversible change over time? Another example of a descriptive question is whether the change in the focal variable is simply a direct quantitative change in magnitude (often referred to as alpha change) or a qualitative change in the conceptualization (often referred to as gamma change) of the construct of interest (Chan, 1998a; Golembiewski, Billingsley, & Yeager, 1976). For example, in newcomer adaptation research, an interesting question concerns whether organizational commitment is changing in strength only (alpha change) or it is changing in dimensionality (gamma change) over time.

The descriptive question is concerned with the "what" or "how" of the change trajectory. The explanatory question focuses on the "why" by seeking to understand and predict the pattern of intra-unit (e.g., intra-individual) change over time described by (i.e., obtained from) the data. The variation to be explained or predicted here is typically the inter-individual differences in intra-individual changes over time. Consider the case where all individuals follow a positive linear trajectory of change in job performance but differ in the rate of change (i.e., slope). If this inter-individual variation in rate of change is systematic and not due to measurement error, then addressing the explanatory question may involve seeking to understand and predict the variation by incorporating one or more explanatory variables (e.g., cognitive ability) in the model of change and estimating their predictive validity. The explanatory variable can either be a time-invariant or time-varying predictor.

It is evident from the above discussion, as well as the earlier discussion on multilevel issues, that understanding changes over time in a focal variable requires us to adopt a multivariate approach such that we can go beyond *describing* the intra-individual changes (in terms of the means and variances of the growth parameters associated with the functional form of the trajectory) to *explaining* these changes by identifying relevant predictor or criterion variables (time-invariant or time-varying) that are correlated with the inter-individual differences in the intra-individual changes. Indeed, in modeling change over time, the primary purposes are describing the nature of the trajectory of change and attempting to account for the inter-individual differences in the functional forms or parameters of the trajectories by relating them to explanatory variables that may be in the form of experimentally manipulated or naturally occurring groups, time-invariant predictors, time-varying correlates or the trajectories of a different variable. LGM and its extensions to examine multivariate and multiple group situations, which are implemented in a latent variable modeling framework, are well suited to address these issues. This section explicates the issues and advances in multivariate approaches to modeling changes over time and the next section examines multiple group issues.

To understand multivariate models of changes over time, we first need to have good grasp of the issues concerning how adequate univariate models can be specified to assess changes over time and subsequently combined to form multivariate models. LGM provides a unified and flexible framework for this purpose. Technical discussions of the data analytic issues are readily available in Chan (1998a). Hence, it suffices to provide a conceptual overview below to serve as the basis for discussing multivariate issues in modeling changes over time. I first introduce the LGM framework, beginning with the basic univariate growth model and how time-invariant predictors can be incorporated in the model, and then explicate the different types of multivariate growth models that can be specified to address more complex situations.

Latent Growth Models

Latent variable approaches are well suited for longitudinal modeling. They are highly flexible and powerful because a variety of latent variable models (i.e., structural equation models) can be fitted to the longitudinal data to describe, in alternative ways, the change over time. LGM, which is implemented using a latent variable approach, offers a direct and comprehensive assessment of the nature of true intra-individual changes and inter-individual differences in these changes. LGM also allows these differences to be related to individual predictors. An LGM can be elaborated into a multiple-indicator latent growth model, in which the focal variable of change is modeled as a latent variable represented by multiple indicators, thereby allowing both cross-sectional and longitudinal measurement errors to be modeled directly and assess whether the extent of distorting effects, if any, that these measurement errors have on the parameter estimates of true change. Technical details of LGM and multiple-indicator LGM are described in Chan (1998a).

LGM represents the longitudinal data by modeling inter-individual differences in the attributes (i.e., parameters) of intra-individual changes over time (i.e., individual growth curves). In an LGM analysis, we can estimate the means and variances of the two growth parameters (intercept and slope factors) and examine if the two parameters are correlated with each other. The LGM analysis can also be used to examine associations between the growth parameters and predictor variables. The predictor could be time-invariant variables such as cognitive ability or personality variables. For example, in newcomer adaptation research, we can use LGM to predict initial status and rate of change in information seeking from proactive personality (Chan, 2000; Chan & Schmitt, 2000). The predictor could also be time-varying variables. When the predictor variable varies over time, it is possible to specify the predictor as a separate univariate LGM (i.e., to model the predictor's change trajectory) and combine it with the original univariate LGM to form a multivariate growth model known as an associative model (see section below on multivariate latent growth models).

Multivariate Latent Growth Models

To conceptualize and assess the relationships between different variables simultaneously as they change over time, different univariate LGMs can be combined to form a multivariate LGM. There are at least three types of multivariate LGMs: associative models, factor-of-curves models, and curve-of-factors models (McArdle, 1988). The associative model is the simplest and most commonly studied type of multivariate model. It involves a direct estimation of the associations between the growth factors of the different univariate models. The factor-of-curves model and the curve-of-factors model extend the conceptualization of the relationships between the univariate models by describing the growth factors, in different ways, in terms of higher order latent growth factors. In each of the three multivariate models, one or more predictors can be included to estimate structural effects from predictors to latent growth factors.

In the associative model combining two univariate LGMs representing variables A and B, respectively, the between-variable associations of the growth factors (i.e., Intercept_A–Intercept_B, Intercept_A–Slope_B, Slope_A–Intercept_B, Slope_A–Slope_B) are directly estimated. Hence, by fitting an associative model, parameters from different change trajectories can be correlated to examine cross-domain associations (i.e., relationships between two focal variables being examined for intra-individual change over time). For example, in their study of newcomer adaptation, Chan and Schmitt (2000) specified associative models in which rate of change in proactivities (e.g., relationship building) was correlated with rate of change in adaptation outcomes (e.g., social integration). One or more predictors (e.g., personality traits) can also be included in the associative model, thereby allowing hypotheses regarding differential predictions (using the same individual predictor) of intra-individual change across domains can be tested. In Chan and Schmitt, proactive personality and previous transition experiences were incorporated in the associative model to simultaneously predict intra-individual changes in both proactivities and adaptation outcomes.

Chan, Ramey, Ramey, *et al.* (2000) provide another illustration of how the associative model incorporating predictors of change may be used to examine complex cross-domain (i.e., multivariate) relationships. In this study, the authors examined the change trajectories of children's social skills in home versus school settings, as well as family predictors of these changes. The study tracked 378 children at four time points, spaced at 12-month intervals over a 4-year period, from Kindergarten to Grade 3. Results showed systematic between-settings differences in children's social skill development. The trajectory of social skills development at home had a different functional form compared with the trajectory at school. In addition, across settings, there were differential patterns of associations between growth parameters and individual predictors including family income, parent education, and child verbal skills.

The findings were invariant across gender groups. Substantively, the study obtained evidence for the context specificity of the children's social skill development process. Although the precise nature of the context specificity of the development process and the contextual influences on the process was not addressed in the study, the application of the multivariate LGM framework provided a new direction to empirically examine children's social skill development as a multifaceted process involving variables interrelated in a dynamic manner. The analysis provided a unified framework for structuring these dynamic relationships. This in turn allows researchers to systematically identify the antecedents, correlates, and consequents of the different aspects of the children's social skill developmental process. For example, we can examine *antecedents* of change such as family or school characteristics, *correlates* of change such as child cognitive growth and changes in peer relations, and *consequents* of change including proximal outcomes such as child-subjective well-being and school achievement, and distal outcomes such as subsequent development of close relationships and personality development.

The associative modeling framework adopted by Chan and Schmitt (2000) and Chan, Ramey, Ramey, *et al.* (2000) may be similarly applied to many areas of I/O psychology to examine multivariate relationships linking job performance, work attitudes, and other work-relevant variables. For example, in the study of dynamic performance, we can fit an associative model to examine whether the trajectory of intra-individual changes for contextual performance has the same or a different functional form as the trajectory for task performance. Predictors such as cognitive ability and personality traits may be incorporated in the associative model to assess if each predictor has similar or differential effects in predicting the growth parameters across the two performance dimensions. We can also examine antecedents of performance change such as previous work experiences and training interventions, correlates of performance change such as changes in self-efficacy and organizational commitment, and consequents of performance change such as subjective well-being and advancement in the organization.

The factor-of-curves model combines univariate LGMs by specifying common higher order growth factors (second-order intercept and slope/shape factors) to account for the (first-order) growth factors of the univariate models, so that growth features that are common across univariate models as well as those that are specific to the univariate models are described. In a factor-of-curves model describing linear growth, a second-order intercept factor is specified to account for the covariation between the intercept factors of the univariate models. Similarly, a second-order slope factor is specified to account for the covariation between the slope factors of the univariate models. The two second-order growth factors (intercept and slope) are allowed to covary. The factor-of-curves model is similar in logic to the familiar hierarchical factor model in confirmatory factor analysis, except that the factors in the factor-of-curves model are growth or chronomic (time-based) factors rather than static common variance factors. The interpretation of the higher order growth factors, however, is conceptually similar to the higher order factors in confirmatory factor analysis in so far as they are higher order common factors postulated from the same measures (i.e., without including additional measures beyond the measures from which the lower order factors were derived) to account for the covariation of the lower order factors. The conceptual meaning of the second-order growth factors in the factor-of-curves model is dependent on the nature of the variables in the univariate models that were combined. For example, if the three univariate models being combined were modeling changes over time in use of alcohol, marijuana, and tobacco, respectively, then the common second-order growth factors may be interpreted as representing the intercept and slope of a higher order substance use construct (Duncan, Duncan, & Strycker, 2006). Similar to the associative model, predictors may be incorporated into the factor-of-curves model to account for the lower order and higher order growth factors.

Clearly, the factor-of-curves model may be applied to many job performance and work attitudes variables. For example, in a study of the dynamics of OCBs, we can track changes in each of the five dimensions of OCBs (altruism, courtesy, civic virtue, compliance, sportsmanship) by first separately fitting a univariate LGM to each OCB dimension to examine the functional form of the trajectory and estimate the growth parameters. The five univariate LGMs may be combined to form an associative model to examine the pairwise between-dimensions covariations of the growth factors. With five univariate LGMs of OCB (each model having an intercept and a slope), there are altogether 40 between-dimensions factor covariations (and five within-dimensions factor covariations) to be estimated in the associate model. Although these 40 between-dimensions factor covariations may be used to describe the growth relationships across the five OCB dimensions and the 40 growth relationships between OCB dimensions can be compared in terms of their strength of association, it is difficult to provide a parsimonious account of the growth relationships among the five OCB dimensions due to the large number of parameter estimates of inter-factor relationships. Now, if all or most of the 40 between-dimensions covariations were significant and substantial, we would conclude that changes in the OCB dimensions were related to each other and a reasonable next question to ask would be whether a common OCB construct, with its intra-individual changes represented by higher order growth factors, could be postulated to account for the between-dimensions factor covariations.

Accordingly, we can fit to the combined OCB data a factor-of-curves multivariate LGM of OCBs combining the five univariate LGMs. This is accomplished by specifying one second-order intercept factor and one second-order slope factor, with each factor causing the five corresponding first-order (intercept/slope) factors. The mean and variances of the second-order growth factors together describe the trajectory of the common OCB construct underlying the five OCB dimensions. Note that the OCB dimension-specific (i.e., first-order) growth parameters are also estimated in the multivariate model. Hence, the factor-of-curves model of OCB allows us to assess changes over time that are specific to each OCB dimension, as well as changes over time that are common across OCB dimensions as represented by changes in the underlying single OCB construct. The 10 coefficients associated with the structural paths from the second-order growth factors to the corresponding first-order factors (five paths for intercepts and five paths for slopes) represent the extent to which the growth factor of the underlying common OCB construct could account for the corresponding growth factor of the respective OCB dimensions. In addition, predictors such as personality traits may be incorporated into the multivariate model to predict the second-order growth factors representing the common OCB construct, in addition to the first-order growth factors of the different OCB dimensions. Hence, by fitting the factor-of-curves model of OCBs incorporating personality traits as predictors, we may be able to isolate the different aspects of OCBs that are associated with different personality traits and to different extent.

The third type of multivariate LGM is the curve-of-factors model (McArdle, 1988), which is mathematically identical to what Chan (1998a) referred to as multiple-indicator LGM. Although mathematically identical, McArdle (1988) and Duncan, Duncan, and Strycker (2006) focused on the multivariate aspects of the model whereas Chan (1998) focused on the measurement errors and measurement invariance aspects of the model. The two different foci are explicated as follows.

Using the substance use example described above, Duncan, Duncan, and Strycker (2006) combined the three univariate LGMs describing alcohol, marijuana, and tobacco use, respectively, into a curve-of-factors model. This is accomplished by first treating the three different substances within the same time occasion as multiple indicators of the time-specific latent factor (i.e., a common variance factor, not a growth factor) called substance use, and then using these first-order time-specific latent factor scores to form the trajectory of changes in substance use defined by the second-order growth factors (intercept and slope). Hence, unlike the associative model and the factor-of-curves model, both of which simultaneously specify the trajectories of different variables and examine the relationships between trajectories of different variables, the curve-of-factors model specifics the trajectory of one variable in which the intercept and slope factors are second-order factors derived from the time series of factor scores where each time point is a first-order factor measured by multiple indicators. Predictors may be incorporated into the model to predict the second-order factors (intercept and slope) or the first-order factors (i.e., the construct within a specific time point). Applying to the OCB example, the curve-of-factors model would specify that the five different OCB variables within each time point are multiple indicators of the same single OCB construct (common variance latent factor) within that time point, and the trajectory of this single OCB construct would be defined by the intercept and slope factors (second-order factors) in the model. Predictors such as personality traits may be incorporated to predict the growth parameters of the OCB construct or the OCB construct within a specific time point. Note that in the curve-of-factor model, OCBs are construed as multiple indicators of a single OCB construct as opposed to measures of different distinct OCB constructs.

Although the curve-of-factors model is referred to as a multivariate growth model by Duncan, Duncan, and Strycker (2006), it is multivariate only in the sense that there were multiple variables repeatedly measured over time. These different variables were combined into the curve-of-factors model by treating the different variables as multiples indicators of the same construct and it is the intra-individual change in only this construct that is being modeled. In contrast, for the associate model and the factor-of-curves model, the different variables repeatedly measured over time were modeled as distinct constructs undergoing intra-individual changes, as represented by the different univariate LGMs combined into the multivariate model.

Rather than describing it as a multivariate growth model, Chan (1998a) construed the curve-of-factor model as a multiple-indicator LGM and emphasized the value of the model in addressing fundamental questions on changes over time relating to different types of measurement errors and different issues of measurement invariance over time. As noted by Chan (1998a; 2002a,b) and others (e.g., Duncan, Duncan, & Strycker, 2006), early work on LGM has not considered issues of measurement errors and measurement invariance. Chan (1998a) showed how LGM can incorporate measurement errors and measurement invariance concerns in the model specification by extending the LGM to a multiple-indicator LGM in which the focal variable of change is modeled as a latent variable assessed by multiple indicators (i.e., a curve-of-factors model) as opposed to a manifest variable, typically the case in prior work on LGM. The use of multiple indicators in an LGM allows both random and nonrandom measurement errors to be taken into account when deriving the intercept and slope/shape factors. The use of multiple indicators to assess the focal construct allows reliable (nonrandom) variance to be partitioned into true score common (construct) variance and true score unique variance. True score unique variance is nonrandom and it is that portion of variance in a measure that is not shared with other measures of the same construct. In LGM, the same measures are repeatedly administered over time. Hence, a failure to partition nonrandom variance into true construct variance and unique variance leads to distorted (inflated) estimates of true change in the focal construct over time. Because only scale/composite level but no item-level (multiple-indicator) information on the focal variable is used in the standard LGM, the standard LGM procedure does not provide the isolation of nonrandom error variance from reliable variance and it takes only random errors into consideration. The use of multiple-indicator LGM addresses the problem.

To understand measurement invariance over time, it is useful to refer to the three types of change distinguished in Golembiewski, Billingsley, and Yeager

(1976): alpha, beta and gamma changes. Alpha change refers to changes in absolute levels given a constant conceptual domain and a constant measuring instrument. For example, if organizational commitment was adequately measured both at Time 1 and Time 2 in terms of reliability and validity such that the same construct was measured at both time points and with the same precision, then the difference in the commitment scores between the two time points represent an alpha change in organizational commitment and the change may be directly interpreted as a change in the absolute level of organizational commitment. We can meaningfully speak of alpha change only when there is measurement invariance of responses across time.

Measurement invariance across time exists when the numerical values across time waves are on the same measurement scale. Measurement invariance could be construed as absence of beta and gamma changes. Beta change refers to changes in absolute level complicated by changes in the measuring instrument given a constant conceptual domain. Beta change occurs when there is a recalibration of the measurement scale. That is, in beta change, the observed change results from an alteration in the respondent's subjective metric or evaluative scale rather than an actual change in the construct of interest. For example, because of the rater's increased leniency in ratings over time, a rating of 6 given at Time 2 may be defined by the rater as was rating of 5 at Time 1. Gamma change refers to changes in the conceptual domain. Gamma change (i.e., change in the meaning or conceptualization of the construct(s) of interest) can take a variety of forms. For example, in the language of factor analysis, the number of factors (a factor representing a construct) assessed by a given set of measures may change from one time point to another. To illustrate, in a study of changes in performance over time, performance may undergo a type of gamma change represented by factorial integration of performance measurement so that performance components (factors) become increasingly interrelated over time such that performance at early time points are best represented as multiple distinct and relatively uncorrelated factors, at mid time points are best represented as multiple highly correlated factors and at later time points are best represented as a single factor.

Chan (1998a) demonstrated how the fundamental questions on measurement errors, measurement invariance, functional forms of intra-individual changes, and other fundamental questions on change over time may be answered in an integrative two-phase latent variable analytical procedure that combines longitudinal means and covariance structures analysis and multiple-indicator LGM. In Phase 1 of the procedure, longitudinal mean and covariance analysis, which is similar to longitudinal factor analysis except that both the indictor intercepts and factor means are also estimated, is used to examine issues of measurement invariance across time and across groups. Establishing invariance provides evidence that results of subsequent growth modeling constituting Phase 2 of the procedure are meaningful. By building invariance assessments as the first logical step to longitudinal modeling, this integrative procedure contrasts with the analytical models that left untested the assumption of measurement invariance across time or groups. In addition to invariance assessments, Phase 1 of the procedure helps in the preliminary assessment of the basic form of intra-individual change by identifying the constraints on the patterns of true score (factor) means and variances over time. In Phase 2, multiple-indicator LGM is used to directly assess change over time by explicitly and simultaneously modeling the group and individual growth trajectories of the focal variable as well as their relationships to other time-invariant predictors and/or time-varying correlates (i.e., growth trajectories in a different domain). As explained in Chan (1998a), longitudinal mean and covariance analysis and multiple-indicator LGM together provide a unified framework for directly addressing the various fundamental questions on change over time.

MULTIPLE GROUP ISSUES

An adequate longitudinal assessment of job performance or work attitude variables should be able to answer questions on whether the intra-individual changes over time are occurring in same or different ways between groups and, if different, in what specific ways the groups differ. A powerful advantage of the LGM method (univariate or multivariate) is that, because it is implemented in the structural equation modeling framework, it allows multiple groups to be assessed simultaneously to test for between-group equality or differences in specific parameters of change. That is, LGMs can be fitted simultaneously to different groups of individuals and multiple-group LGM analyses can be performed to test for across-groups invariance of one or more of the specified relationships in the LGM.

The groups under comparisons could be experimental groups (e.g., randomly formed groups of participants assigned to different task conditions) or natural occurring groups such as male and female incumbents. The question of interest is whether a specific intra-individual change pattern found in one group is equal to, or differs from, in either magnitude or form, the intra-individual change pattern in a different group. For example, the growth trajectory representing changes in performance on a given job over time may differ in functional form between male and female incumbents. Alternatively, males and females may share the same functional form but they differ in the rate of change in job performance. As another example, employees who have completed a training program may undergo a type of gamma change represented by factorial integration of performance measurement so that performance components (factors) become increasingly inter-related over time whereas employees who completed a different training program may exhibit factorial invariance so that inter-correlations among performance components remain constant over time. Another between-groups comparison question concerns whether change is uni-path or multi-path in each group. Change can be represented as proceeding in one single pathway or through multiple different pathways. Multiple paths occur when a detour from a single growth trajectory path is possible as individuals proceed from one time point to another. For example, when proceeding from Time 1 to Time 4 (through Times 2 and 3), assume some individuals follow a linear trajectory but others follow a quadratic trajectory. Using the multiple-group LGM approach, we would be able to examine if the growth trajectories of distinct groups of individuals being tracked over time follow the same or different functional forms. The multiple-group LGM is highly flexible as it has the capability to simultaneously model and compare across distinct groups the various specific facets of intra-individual change patterns.

Within the population of interest, if the subpopulations characterized by different intra-individual change patterns are observable subgroup membership variables that are known a priori such as groupings by demographics (e.g., sex, ethnicity), then the longitudinal assessment, as explained above, is quite easily performed by applying multiple-group LGMs to isolate the data according to the subgroup membership variable. However, if the subpopulations characterized by different intra-individual change patterns are unobserved (i.e., latent) in the sense that subgroup membership (how many subgroups and which subgroup does an individual belong to) is not known a priori but latent and empirically derived from the individual's values on a set of variables, then it is not possible to perform a straightforward multiple-group LGM analysis because there is no known subgroup membership variable. Fortunately, with recent methodologic advances in growth modeling, we can now model such unobserved heterogeneity in the population. Specifically, a class of longitudinal techniques known as general growth mixture modeling developed by Muthén (2004) offers an inclusive framework that combines latent growth models and latent class models. This general framework allows the researcher to identify latent classes characterized by different patterns of latent growth. These mixture models are useful because they allow us, in a single integrated analysis, to identify unobserved groups of individuals with qualitatively different growth trajectories by establishing the number of latent subpopulations, the distinct intra-individual change patterns associated with the latent subpopulations, and assigning latent subpopulation membership to individuals. For discussions on technical issues and an empirical example on the growth mixture modeling method, see Wang and Chang (in press). Growth mixture modeling is a flexible framework that could be applied to many areas of study in I/O psychology and the logic of the technique allows us to open up new and fruitful avenues for future research such as identifying latent subpopulations with distinct intra-individual change patterns in various domains such as task performance, OCBs, and withdrawal behaviors.

Finally, latent subpopulations and observed groupings may be combined in a single analysis to examine more complex multiple group issues. Specifically, the growth mixture modeling method for examining latent subpopulations may be extended to fit data simultaneously to multiple observed (known a priori) groups. For example, we can examine whether the number and characteristics of latent subpopulations are the same or different across gender groups, a multiple-group growth mixture modeling analysis may be conducted to estimate growth mixture models simultaneously for the male and female groups. The logic for the analysis is similar to the standard multiple-group latent variable method in which specific parameters may be fixed to equal or allowed to vary freely across multiple observed groups to produce different multiple-group growth models for nested model comparisons to determine the most appropriate multiple-group model (Chan, 1998a). With appropriate cross-cultural theories, this integrative analytic method combining growth mixture modeling (to identify latent subpopulations) and observed multiple-group latent variable modeling provides a powerful method to examine new substantive research questions on cross-cultural differences in intra-individual changes in terms of possible cross-cultural differences in latent subpopulations of intra-individual change patterns.

CONCLUSIONS

For many decades in I/O psychology, predictor–criterion relationships have been described in terms of static models without much attention paid to the temporal aspects of the predictor–criterion constructs including what and how changes may occur over time. Consider the example of job performance models. An individual's job performance may change over time in various ways (e.g., increase/decrease in level, changes in the number/nature of underlying dimensions) and these intra-individual changes are important for understanding, predicting, and evaluating job performance. For example, when performance changes over time either in terms of level or dimensionality, using a sample of job incumbents with varying levels of job tenure in a validation study could affect and confound estimates of validity and the interpretation of predictor–criterion relationships. When there exists between-group differences, either in terms of observed subgroup membership or latent subpopulations, a longitudinal assessment method that assume population homogeneity in intra-individual change patterns will lead to incomplete or even misleading substantive inferences.

Advances in longitudinal analytical strategies, especially those that involve latent variable modeling as explicated in this article, allow us to make more direct and better connections linking theory, measurement, data, and interpretation. As shown in this article, when suitably applied, the analytical advances provide us both the conceptual basis and statistical method to hypothesize, test, and interpret intra-individual changes over time in the predictor and criterion variables in the context of multilevel, multivariate, and multiple group issues, which in turn allow us to derive adequate substantive implications and make effective practical recommendations concerning job performance and work attitudes.

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